Evaluation of color representation for texture analysis

E.L. van den Broek E.M. van Rikxoort

NICI, Radboud University Nijmegen
P.O. Box 9104, 6500 HE Nijmegen

Abstract

Since more than 50 years texture in image material is a topic of research. Hereby, color was ignored mostly. This study compares 70 different configurations for texture analysis, using four features. For the configurations we used: (i) a gray value texture descriptor: the co-occurrence matrix and a color texture descriptor: the color correlogram, (ii) six color spaces, and (iii) several quantization schemes. A three classifier combination was used to classify the output of the configurations on the VisTex texture database. The results indicate that the use of a coarse HSV color space quantization can substantially improve texture recognition compared to various other gray and color quantization schemes.

1 Introduction

Texture, as feature for the human visual system, reveals scene depth and surface orientation. Moreover, it describes properties like smoothness, coarseness, and regularity of a region. Among other features, humans use these "quite effectively", as Rosenfeld [10] (p. 314) stated. So, he concluded: "computer vision is feasible" [10] (p. 314). With respect to texture, the latter was illustrated by the numerous texture analysis algorithms, developed in the last 50 years [10].

However, most texture analysis techniques developed, can only deal with gray-scale images. As Palm [9] already denoted: "The integration of color and texture is still exceptional". Mäenpää and Pietikäinen [8] and Palm [9] recently determined that color is of importance in texture recognition. In their research they used different color spaces and quantization schemes.

This research, on the one hand, extends their approach using six color spaces combined with five different quantization schemes (see Section 3). On the other hand, we are interested in the effect of the precision of quantization schemes for both the gray-scale and color spaces. Two texture analysis techniques are applied: the co-occurrence matrix and the color correlogram, described in Section 2. The experimental setup and the classifiers used, are described in Sections 4 and 5. This paper ends with the results and the discussion in Section 6 and 7.

2 The co-occurrence matrix and color correlogram

The co-occurrence matrix is found to be a good texture analysis method [11, 13]. Huang et al. [4] extended the co-occurrence matrix to the color domain with the introduction of the color correlogram. In this section the co-occurrence matrix and color correlogram will be defined. In addition, a pilot study will be described with which we determined what texture features to use for the main experiment.

2.1 The co-occurrence matrix

The co-occurrence matrix is constructed from an image by estimating the pairwise statistics of pixel luminance. In order to (i) provide perceptual intuitive results and (ii) tackle the computational burden, luminance was quantized into an arbitrary number of clusters of luminance values, which we will name: gray values.

The co-occurrence matrix $C_{\bar{d}}(i,j)$ counts the co-occurrence of pixels with gray values i and j at a given distance $\bar{d}$. The distance $\bar{d}$ is defined in polar coordinates (d, α), with discrete length and orientation. In practice, α takes the values $0°, 45°, 90°, 135°, 180°, 225°, 270°,$ and $315°$. The co-occurrence matrix $C_{\bar{d}}(i,j)$ can now be defined as follows:

$$C_{\bar{d}}(i,j) = \Pr(\mathrm{I}(p_1) = i \wedge \mathrm{I}(p_2) = j \mid |p_1 - p_2| = \bar{d}), \quad (1)$$

where Pr is probability, and p_1 and p_2 are positions in the gray-scale image I. Let N be the number of gray-values in the image, then the dimension of the co-occurrence matrix $C_{\bar{d}}(i,j)$ will be $N \times N$. This algorithm yields a symmetric matrix, which has the advantage that only angles up to 180° need to be considered. One co-occurrence matrix is defined for each distance ($\bar{d}$) by averaging the four co-occurrence matrices of the different angles (i.e., 0°, 45°, 90°, and 135°).

Because of the high dimensionality of the matrix, the individual elements of the co-occurrence matrix are rarely used for means of texture analysis. Instead, a large number of textual features can be derived from the matrix, such as: energy, entropy, correlation, inverse difference moment, inertia, Haralick's correlation [3], cluster shade, and cluster prominence [1]. These features characterize the content of the image.

Note that in order to apply the co-occurrence matrix on color images, these images have to be converted to gray-value images. This conversion will be described in Section 3.

2.2 The color correlogram

In Equation 1, i and j denote two gray-values. For the color correlogram not the luminance is quantized, but a color space is quantized. Subsequently, the color correlogram can be defined by Equation 1, with i and j being two quantized color values (i.e., clusters of colors).

2.3 Feature selection for gray-scale texture analysis

To determine which feature-distance combinations perform best, a pilot study was done on gray-value texture analysis, using the MeasTex database[1] as texture database and the co-occurrence matrix as texture analysis method. For each image in the database eight features (i.e., energy, entropy, correlation, inverse difference moment, inertia, Haralick's correlation [3], cluster shade, and cluster prominence [1]) were calculated for four distances $\bar{d}$ (i.e., 1, 2, 5, and 10).

For each distance set, every possible combination of features was fed to a statistic classifier using a linear discriminant function (see Section 5). A 100% classification was found with $\bar{d} = 1$, when a combination of four features (i.e., entropy, inverse difference moment, cluster prominence, and Haralick's correlation) was used. Therefore, we chose this configuration for the main experiment. A detailed report discussing this study is available online [16].

3 Color spaces

A color space specifies colors as tuples of (typically three) numbers, conform certain specifications. One can describe color spaces using two important notions: perceptual uniformity and device dependency. Perceptually uniform means that two colors that are equally distant in the color space are perceptually equally distant. A color space is device dependent when the actual color displayed depends on the device used.

In the remainder of this section, the color spaces with their quantization schemes as used in this experiment, will be described. The quantization of color images transformed into gray-scale images will not be described for every color space since it is equal for every color space: the gray-scale axis is divided in the number of bins needed for the specific quantization scheme.

3.1 The RGB color space

The RGB color space is the most used color space for computer graphics. It is device dependent and not perceptually uniform. Each color-axis (R, G, and B) is equally important. Therefore, each axis should be quantized with the same precision. The conversion from a RGB image to a gray value image simply takes the sum of the R,G, and B values and divides the result by three.

3.2 The HSV color space

The HSV (Hue, Saturation, and Value) color space is more closely related to human color perception than the RGB color space [7], but is still not perceptual uniform. In addition, it is device-dependent.

Hue is the color component of the HSV color space. When Saturation is set to 0, Hue is undefined. The Value-axis represents the gray-scale image. The most common quantization of HSV is in 162 ($18 \times 3 \times 3$) bins.

[1] http://www.cssip.uq.edu.au/meastex/meastex.html

3.3 The YUV and YIQ color spaces

The YUV and YIQ color spaces are developed for television broadcasting. The YIQ color space is the same as the YUV color space, where the I-Q plane is a 33° rotation of the U-V plane. The Y signal represents the luminance of a pixel and is the only channel used in black and white television. The U and V for YUV and I and Q for YIQ are the chromatic components.

The Y channel is defined by the weighted values of R(0.299), G(0.587), and B(0.144) . The YUV and YIQ color spaces are device-dependent and not perceptually uniform. When the YUV and YIQ color spaces are quantized, each axis is quantized with the same precision. In addition, to optimize color appearance the YUV color space is often sampled. The samplings we used to construct the color correlogram are: 4:4:4, 4:2:2, and 4:1:1, where the numbers denote the relative amount of respectively Y on each row, U and V on each even-numbered row, and U and V on each odd-numbered row in the image.

3.4 The CIE XYZ and LUV color spaces

The first color space developed by the Commission Internationale de l'Eclairage (CIE) is the XYZ color space. The Y component is the luminance component defined by the weighted sums of R(0.212671), G(0.715160), and B(0.072169). The X and Z are the chromatic components. The XYZ color space is a device-independent color space, but is perceptually not uniform. In quantizing the XYZ space, each axis is quantized with the same precision.

The CIE LUV color space is a projective transformation of the XYZ color space that is perceptually uniform and device-independent. The L-channel of the LUV color space is the luminance of the color. The U and V channels are the chromatic components. So, when U, and V are set to 0, the L-channel represents a gray-scale image. In quantizing the LUV space, each axis is quantized with the same precision.

4 Method

The texture database used in the experiments is the VisTex[2] texture database, which consists of 19 labeled classes. The classes with less than 10 images were not used in this experiment, which results in four classes: bark (13 images), food (12 images), fabric (20 images), and leaves (17 images). In order to generate more data for the classifiers, we adapted the approach of Mäenpää and Pietikäinen [8], Palm [9], and Singh, Markou, and Singh [12]: the original images were split into four sub-images, resulting in a database of 248 textures. Next, the training and test set for the classifiers were composed using random picking, with the prerequisite that each class had an equal amount of training data. For classification, three classifiers were combined (see Section 5).

The co-occurrence matrix and color correlogram (see Section 2) were used as texture analysis methods in combination with six color spaces (see Section 3), and

[2]http://vismod.media.mit.edu/vismod/imagery/VisionTexture/vistex.html

a set of quantization schemes (see Table 1). For both texture analysis methods, for each color space, five quantization schemes were applied.

Table 1: The quantization schemes applied on the six color spaces, for each texture descriptor. Note that YUV* is sampled for the color correlogram (see Section 3.3).

Color space	**Quantization scheme (in bins)**	
	Co-occurrence matrix	**Color correlogram**
RGB	8, 16, 32, 64, 128	8, 64, 216, 512, 4096
HSV	8, 16, 32, 64, 128	27, 54, 108, 162, 324
YIQ, YUV*, XYZ, & LUV	8, 16, 32, 64, 128	8, 27, 64, 125, 216

5 Three classifier combination

To classify the texture images we used:

1. The statistic classifier is based on discriminant analysis with a linear discriminant function y that decides on class membership. An input vector x is assigned to a class C_k if $y_k(x) > y_j(x)$, for all $j \neq k$.

2. The probabilistic neural network approximates the probability density function of the training examples presented. It consists of three layers after the input layer: the pattern layer, the summation layer, and the output layer. The outcome is a classification decision in binary form.

3. The K-nearest neighbor classifier works with the following algorithm: suppose the data set contains N_k data points in class C_k and N points in total, so that $\sum_k = N$. The classifier then works by drawing a hypersphere around the point to classify, x, which encompasses K points. To minimize the probability of misclassifying x, x is assigned to the class C_k for which the ratio $\frac{K_k}{K}$ is largest, where K_k is the number of points from class C_k. For the present research K was set to 1. Hence, x was assigned to the same class as the class of the nearest point of the training set.

They were combined using the technique of majority voting [6]: when at least two of the three classifiers agree on the class label of a sample texture, this label is given else the label false is given.

6 Results

In Table 2, for both texture descriptors, for each color space, the quantization scheme performing best, with its percentage of correct classification, is provided. For the co-occurrence matrix, the HSV 32 bins, and LUV 8 bins configurations performed best. In combination with the color correlogram, the HSV 162 bins configuration performed best.

The confusion matrices in Table 3 provide the complete results of each of these three configurations. Entrance (i, j) gives the percentage of samples that was classified to class j while they should be classified to class i. In total, 70 different configurations were applied: 30 for the co-occurrence matrix and 40 for the color correlogram.

In addition, it was found that the color correlogram performs better than or equal to the co-occurrence matrix for all color spaces and quantization schemes used. For both the color correlogram and the co-occurrence matrix, the most precise quantization schemes did not perform as good as the more coarse quantizations (see Table 2). The complete results are available online[3].

Table 2: The best classification results (%) of the co-occurrence matrix and the color correlogram, for each color space - quantization scheme (#bins) combination.

Color space	**Co-occurrence**		**Color correlogram**	
	#bins	**%**	**#bins**	**%**
RGB	8	56%	8	68%
HSV	32	58%	162	74%
YIQ	8	54%	125	53%
YUV (4:4:4; 4:2:2; 4:1:1)	8	54%	27; 27; 125	52%; 56%; 52%
XYZ	64	56%	8	71%
LUV	8	58%	27	66%

Table 3: Three confusion matrices in one (from left to right): (i) the co-occurrence matrix in the 8-bins LUV color space, (ii) the co-occurrence matrix in the 32-bins HSV color space, and (iii) the color correlogram in the 162-bins HSV color space.

LUV-8 Co-occurrence matrix					
	Food	**Fabric**	**Leaves**	**Bark**	**False**
Food	70 / 60 / 70	10 / 10 / 10	0 / 0 / 10	20 / 0 / 0	0 / 30 / 10
Fabric	13 / 8 / 0	65 / 78 / 93	0 / 0 / 0	18 / 5 / 3	4 / 9 / 4
Leaves	14 / 14 / 7	0 / 7 / 18	54 / 43 / 71	18 / 7 / 4	14 / 29 / 0
Bark	25 / 25 / 8	17 / 17 / 33	17 / 8 / 17	33 / 25 / 25	8 / 25 / 17

7 Discussion

In the present research, first, a combination of texture features was determined performing best for gray value texture analysis. Next, 70 configurations for texture analysis of color images were compared with each other, using the VisTex texture database. Each configuration can be described by the texture analysis algorithm, the color space, and the quantization scheme used. The classification of the textures was done by a three classifier combination.

For all color space-quantization combinations the color correlogram performed better than or equal to the co-occurrence matrix (see Table 2). This sustained [8, 9] that color is of importance in texture classification, which can be explained by the fact that different colors can have the same luminance.

[3]http://eidetic.ai.ru.nl/egon/publications/BNAIC2004-Complete_results.pdf

The CIE LUV color space was expected to yield the best classification results for the color correlogram, since it was the only perceptually uniform color space. However, the HSV color space performed best. This can be explained by (i) the fact that the HSV color space is approximately perceptually uniform [7] and (ii) the relatively high precision in color (Hue) quantization of the HSV 162 bins scheme.

Further, please note that one of the classes (named Bark) was classified more often incorrect than correct (see Table 3), due to its overlap with features of other classes. This limited the overall classification performance severely. In other studies (e.g., Singh et al.[12]) some classes of the VisTex database were left out for this reason. The use of specialized classifiers can possibly tackle such problems.

An interesting result is the fact that using more bins did not improve performance. In no instance the largest number of bins gave the best results. This result is consistent with the notion of the existence of a limited number of color categories in which one can represent colors [2, 14, 15]. In addition, it is computationally cheap. This, in contrast with the quantization schemes proposed by Mäenpää and Pietikäinen [8] who used quantization schemes with up to 32768 color bins.

With the further optimization of the configuration of the color quantization scheme for the HSV color space and the development of specialized classifiers, we expect to develop an optimized, computationally cheap color texture classifier. Such a classifier can be used in a broad range of settings (e.g., computer/robot vision [10] and content-based image and video retrieval [5, 15]), for image segmentation, shape detection, and for image classification in general [7, 10].

Acknowledgments: The Dutch organization for scientific research (NWO) is gratefully acknowledged for funding the ToKeN2000 Eidetic project (nr. 634.000.001). Further, we would like to express our gratitude to the reviewers for their valuable comments on the manuscript.

References

[1] R. W. Conners, M. M. Trivedi, and C. A. Harlow. Segmentation of a high-resolution urban scene using texture operators. *Computer Vision, Graphics, and Image Processing*, 25:273–310, 1984.

[2] G. Derefeldt, T. Swartling, U. Berggrund, and P. Bodrogi. Cognitive color. *Color Research & Application*, 29(1):7–19, 2004.

[3] R. M. Haralick, K. Shanmugam, and I. Dinstein. Textural features for image classification. *Transactions on Systems, Man and Cybernetics*, 3(6):610–621, 1973.

[4] J. Huang, S. R. Kumar, M. Mitra, W.-J. Zhu, and R. Zabih. Image indexing using color correlograms. In G. Medioni, R. Nevatia, D. Huttenlocher, and J. Ponce, editors, *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 762–768, 1997.

[5] M. Israël, E. L. van den Broek, P. van der Putten, and M. J. den Uyl. Automating the construction of scene classifiers for content-based video retrieval. In L. Khan and V. A. Petrushin, editors, *Proceedings of the Fifth International Workshop on Multimedia Data Mining (MDM/KDD'04)*, pages 38–47, Seattle, WA, USA, 2004.

[6] J. Kittler, M. Hatef, R. P. W. Duin, and J. Matas. On combining classifiers. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(3):226–239, 1998.

[7] T. Lin and H.J. Zhang. Automatic video scene extraction by shot grouping. In *Proceedings of the 15th IEEE International Conference on Pattern Recognition*, volume 4, pages 39–42, Barcelona, Spain, 2000.

[8] T. Mäenpää and M. Pietikäinen. Classification with color and texture: jointly or separately? *Pattern Recognition*, 37(8):1629–1640, 2004.

[9] C. Palm. Color texture classification by integrative co-occurrence matrices. *Pattern Recognition*, 37(5):965–976, 2004.

[10] A. Rosenfeld. From image analysis to computer vision: An annotated bibliography, 1955-1979. *Computer Vision and Image Understanding*, 84(2):298–324, 2001.

[11] M. Sharma and S. Singh. Evaluation of texture methods for image analysis. In R. Linggard, editor, *Proceedings of the 7th Australian and New Zealand Intelligent Information Systems Conference*, pages 117–121, Perth, Western Australia, 2001. ARCME.

[12] M. Singh, M. Markou, and S. Singh. Colour image texture analysis: Dependence on colour space. In C. Y. Suen, R. Kasturi, and R. Plamondon, editors, *Proceedings of the 16th IEEE International Conference on Pattern Recognition*, volume 1, pages 672–676, Quebec City, QC, Canada, 2002.

[13] K. Valkealahti and E. Oja. Reduced multidimensional histograms in color texture description. In *Proceedings of the 14th International Conference on Pattern Recognition*, volume 2, pages 1057–1061, Brisbane, Australia, 1998.

[14] E. L. van den Broek, M. A. Hendriks, M. J. H. Puts, and L. G. Vuurpijl. Modeling human color categorization: Color discrimination and color memory. In T. Heskes, P. Lucas, L. Vuurpijl, and W. Wiegerinck, editors, *Proceedings of the 15th BNAIC*, pages 59–68. SNN, Radboud University Nijmegen, 2003.

[15] E. L. van den Broek, P. M. F. Kisters, and L. G. Vuurpijl. The utilization of human color categorization for content-based image retrieval. In B. E. Rogowitz and T. N. Pappas, editors, *Proceedings of Human Vision and Electronic Imaging IX*, volume 5292, pages 351–362, San Jose, CA, USA, 2004.

[16] E. M. van Rikxoort. Texture analysis. Technical report, NICI, Radboud University Nijmegen; URL: `http://eidetic.ai.ru.nl/egon/publications/Rikxoort04-Texture_analysis.pdf`, 2004.